MRL

QAZVIN ISLAMIC AZAD UNIVERSITY
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Who We Are?

The MRL Agent team has actively participated in RoboCup competitions, including the IranOpen, WorldCup, and Asia Pacific, since 2003. Our primary area of expertise is in developing multi-agent systems for rescue missions. Our team has achieved several victories in various world competitions from 2005 to 2021 in RoboCup competitions, cementing our position as a leading contender in the field

Main Contributions

- ✓ Propose a new approach for Map Clustering
- ✓ Propose search method for ambulance task allocation

Related Works

1. **Clustering:** A machine learning method to group similar data points.
2. **Types:** Hard and soft clustering, and point-assignment or hierarchical models.
3. **k-means:** A commonly used point-assignment method, used in tasks like map clustering.
4. **Our Approach:** Enhanced k-means algorithm for agent decision-making, considering factors like point density and presence of citizens and agents.
5. **Challenge:** Current approach requires tuning based on map size, implying a performance dependency on the input maps.

Map Clustering: Methodology

1. Introduction of a new clustering method: It eliminates the need for initialization or parameter tuning and can adapt to different map sizes.
2. Automatic determination of optimal clusters: The method calculates the optimal number of clusters based on the number of agents and the available map information.
3. Modification of the standard k-means algorithm: A novel unsupervised k-means objective function is employed, which combines values and utilizes cross-entropy theory.
4. Iterative process to achieve stable clusters: The new method iterates to reach a stable number of clusters, addressing the limitations of parameter initialization and dependency on map size.
5. Evaluation of the new method: The performance of the proposed method is assessed using measures of accuracy and computational cost, with results to be discussed in the following section.

Map Clustering: Notations

Section	Formula
Iteration Mechanism	$a_k = \frac{\sum_{i=1}^{n} z_{ik} x_{ij}}{\sum_{i=1}^{n} z_{ik}}$ and $z_{ik} = \begin{cases} 1, if \ \|x_i - a_k\|^2 = \min_{1 \le k \le c} \|x_i - a_k\|^2 \\ 0, otherwise \end{cases}$
Cross-entropy theory	$J_{UKM_2}(z, A, \alpha) = \sum_{i=1}^{n} \sum_{k=1}^{c} z_{ik} \|x_i - a_k\|^2 - \beta n \sum_{k=1}^{c} \alpha_k \ln \alpha_k - \gamma \sum_{i=1}^{n} \sum_{k=1}^{c} z_{ik} \ln \alpha_k$
Lagrangian	$z_{ik} = \begin{cases} 1, if \ \|x_i - a_k\|^2 - \gamma \ln \alpha_k = \min_{1 \le k \le c} \|x_i - a_k\|^2 - \gamma \ln \alpha_k \\ 0, otherwise \end{cases}$
	$a_k^{(t+1)} = \sum_{i=1}^{n} z_{ik} / n + \left(\frac{\beta}{\gamma}\right) \alpha_k^{(t)} - \sum_{s=1}^{c} \alpha_s^{(t)} \ln \alpha_s^{(t)}$
Calculate stable number of clusters	$c^{(t+1)} = c^{(t)} - \left| \left\{ a_k^{(t+1)} \middle| a_k^{(t+1)} < \frac{1}{n}, k = 1, \dots, c^{(t)} \right\} \right|$

Search Strategy: Methodology

1) Generating N random solutions and computing their fitness values for $FEs = N$ that FEs was the number of fitness evaluations

2) A new solution was generated V_i according to Equation 6, for each X_i

3) The probability p_i was calculated by: $p_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i}$

4) All solution X_i was updated by the equation $x_{i,j} = low_j + rand_j \cdot (up_j - low_j)$ If is $max\{trial_i\} > limit$ where $[low_j, up_j]$ is the constraint box, and $rand_j$ is a random value generated in the range [0,1].

5) The procedure was stopped if $MaxFEs$ were the maximum value of FEs.

Search Method for Ambulance Task Allocation

Subject	Formula
Multi-Objective Optimization	$\min\big(f_1(\vec{x}), f_2(\vec{x}), \dots \dots \dots, f_n(\vec{x})\big)$
objective functions	$ORS = \arg\min\{\min\big[CR_r, FR_r, WR_r\big], min[CR_d, FR_d, WR_d]\}\}$
objective functions	$CR = \sum_{i=1}^{n}\sum_{j=1}^{k}\lvert r_j - a_i\rvert^2$ $\quad FR = \underset{1<j<k}{min} r_j(qwt)$ $\quad FR = \underset{1<j<k}{min} r_j(nb - nc)$

Experimental Setups

Experiment Setup:

- Core i7-8700K
- 32 GB of RAM
- Ubuntu

Measurement Metrics:

$$accuracy = \frac{number\ of\ recognized\ clusters\ by\ proposed\ method}{number\ of\ truth\ clusteres\ in\ the\ map}$$

Experiment Results

Performance analysis of the proposed method against a standard K-Means algorithm

MAP NAME	STANDARD K-MEANS	PROPOSED METHOD
Montreal	71%	**91%**
SF2	91%	**93%**
Sydney2	72%	**90%**
Berlin3	70%	**94%**
Kobe3	92%	**91%**
Sakae2	89%	**90%**
Eindhoven3	90%	**95%**
Paris3	**87%**	**91%**

Experiment Results

Performance analysis of the proposed method against the Artificial Bee Colony algorithm

Map Name	Artificial Bee Colony	Proposed Method
Montreal	37.00	**40.85**
SF2	21.00	**23.68**
Sydney2	04.85	**07.14**
Berlin3	17.81	**34.60**
Kobe3	18.15	**34.05**
Sakae2	54.04	**58.45**
Eindhoven3	43.36	**45.90**
Paris3	**57.07**	**76.23**

Summary

This study aimed to improve the performance of the search strategy for finding optimal regions in small and large maps, with the incorporation of a new multi-objective decision-making system and a free-of-initialization map clustering module. The experimental results showed a significant improvement in the map clustering system for both small and large maps, and the scores were shifted through adjustments to the new search function. Future research will focus on improving the computation cost of the proposed map clustering system to enable its application to real-time tasks. Overall, this study presents a promising approach for enhancing the efficiency and effectiveness of search strategies for optimal region detection.

Thanks for your attention